Potential Formulation for Aeroelastic Constraint Analysis in a Conceptual Design Environment

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Abstract

The paper defines an innovative, novel design methodology that results in a product that effectively satisfies the designer's needs and requirements. Use is made of the response surface methodology after consideration of other metamodeling techniques. Drawbacks of the response surface methodology are mitigated by incorporating sensitivity information in the response surface creation. The definition, application, and eventual implementation of this emerging design tool for new product design is described. The new methodology envisioned will make use of the bi-level integrated system synthesis decomposition for distributed computing. The overall goal is to accomplish cheaper, faster, better designs for structural systems and components. This research leads to the discussion of the use of design tools for structural optimization, including the dynamic aeroelastic constraints.

Introduction

During the early decades of powered flight, the term 'aeroelasticity' was never heard of. Surprisingly enough though, the field of aeroelasticity is older than the era of powered flight.[1] The design-for-aeroelasticity research field became important after Roxbee Cox, Pugsley, Frazer, Duncan etc. identified the mechanism of flutter and developed essential mathematical tools to treat aeroelasticity.[1] With ever faster and higher flying airplanes during the 40s, 50s and 60s, culminating with the design of the Concorde in the commercial arena, aeroelasticity played an ever more important role in design. Nowadays, design of flight vehicles without the consideration of aeroelastic properties is unthinkable.

Next to the consideration of dynamic aeroelasticity and simplified models, another reason for developing this new tool is found in recent interest in revolutionary concepts: oblique wing, no-tail configurations, blended wing-body. Historically regressed design databases become obsolete as new technologies are introduced and new vehicle classes are investigated. Since most sophisticated analysis codes are too computationally expensive for iterative application, the designer is faced with a lack of information, limiting his sound decision making ability.[2]

Motivation and Background

In the next subsections the following questions will be addressed as an introduction to the research.

1. How do designers go about structural design-for-aeroelasticity at the conceptual and preliminary level?
2. To realize an improvement, what has to change in the architecture, problem formulation, or approach?
3. What new design tools are needed to achieve that change?

Design for aeroelasticity at early design level

This section focuses on how today a designer goes about designing a new airplane, addressing questions of the type: What are the current design practices, what are his sources of information, and why was/is it done that way.

Conceivably, there are three ways to approach "design-for-aeroelasticity". The first one is a special case with aeroelasticity being an after-thought. Although still possible today, this design practice has vanished in all but the experimental (kit-built) and

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slow general aviation airplane design since the discovery and maturing of the aeroelasticity research domain. The second design practice starts from an optimized structural geometry and aeroelastic ingenuity is applied to comply with regulations and requirements. Although this approach works well, it typically results in a sub-optimal design. The third practice would be a structural optimization concurrently executed with the aeroelastic analysis. The reasons for this being the best option as far as achieving optimality will become clear throughout the exposition.

Most, if not all designs perform an aeroelastic optimization of an already optimized flight vehicle (the second option above). There are a couple of reasons for the popularity of these design practices. Firstly, most vehicles are extensions or modifications to already existing geometries (i.e. families of vehicles). Secondly, the vehicle to be designed is a conventional configuration (*cookie cutter designs*), for which the eccentric aeroelastic behavior and problem areas are well-known. The above was also realized by Komarov et al.[3]

Consequently, classical aeroelastic effects (i.e. divergence, flutter, aileron reversal etc.) are today mainstream in design, analysis and certification.[4] Simple, basic information on aeroelasticity and the impact of structural changes on an airplane are still very fuzzy relationships and based on empirical knowledge.The effect of spar and rib placement, or how to prevent flutter by changing the sweep are fairly well documented for traditional aircraft. This all promotes the feeling that aeroelasticity has become of lesser importance.

However, it is not uncommon for an initial wing design to have unacceptable aeroelastic behavior due to the ignorance of aeroelastic analysis at the conceptual design stage. This problem is then corrected in an *ad hoc* manner, resulting in a sub-optimal design.[5] Furthermore, there are many areas where aeroelastic effects are so pervasive and new that progress has to be made if the design frontier for higher performance flight vehicles is to be expanded.[4] Komarov et al describe the need (in a different problem setting) as follows: the ability to generate *scientific* estimates of component weights that are not tied too closely to a historical database is a key need for exploring new design spaces.[3]

In other words, there is a need for a capability of generating that information and filling up that information gap if new configurations are to be investigated successfully. The current design practices all have one thing in common: the state of affairs does not bring aeroelasticity to the fore-front of the design phase.

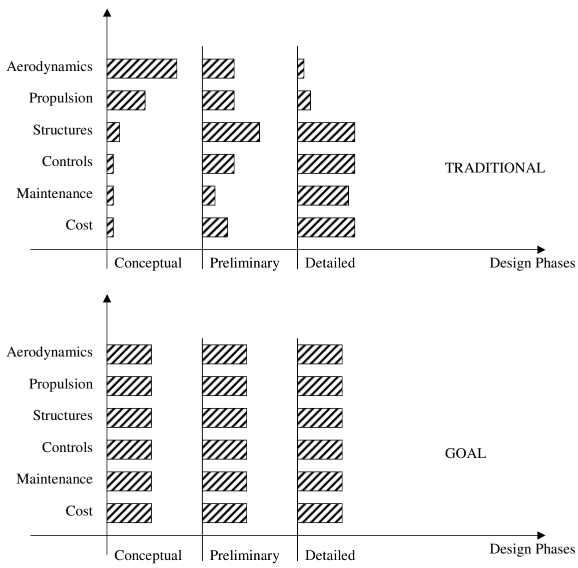


Figure 1: Design Process Effort Distribution

Methods to Design for Aeroelasticity

Take a look at the current design practices. Note that because the structural layout is defined late, it is near to impossible for the structure to have a major influence on the early design process[6] (refer to Figure 1). Taylor et al go on to say that if designers are serious about cost as an independent variable (CIAV), they must have the means to do these trade offs. Treatment of the structure with physics-based design tools is a necessary requirement to achieve that goal.[6]

Dynamic aeroelasticity is probably the single most important aeroelastic constraint in the design environment. Zink et al. indicate that Boeing's Supersonic Transport (SST) design in the 70s and the recent NASA High Speed Research (HSR) programs left the flutter problem untouched. Both research groups concluded that flutter would be determined in the prototype development phase.[7] Zink et al go on to state that it is at this early design stage that the complex problem can be most effectively and economically addressed. Weisshaar puts it clearly as follows: consideration and *prediction* of aeroelastic effects are essential for the efficient design of high performance flight vehicles.[4]

Another important point was made by Taylor et al: if an analysis tool is to become a "design tool" it must add value by providing technical support for design decisions. Furthermore, analytical tools al-

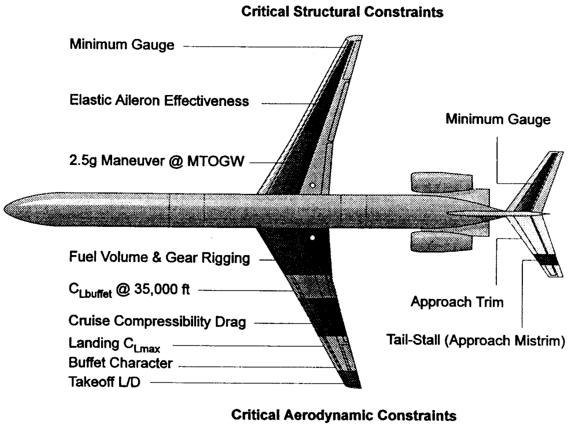


Figure 2: Example of Critical Constraints On An MD-90 Wing Design Exercise[8]

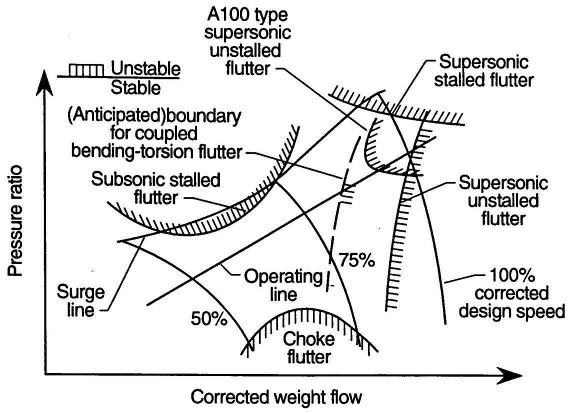


Figure 3: Example of Constraints in a Design Environment for a Compressor[9]

ways create data. To be useful this data needs to be presented to the process as communicable and descriptive information at the right time.[6] A good example of providing clear, concise data to the designer is shown in Wakayama et al and depicted in Figure 2.

What can be done to improve the process and render it more efficient. It becomes clear that what is needed is a mathematically founded, transparent methodology to calculate these relationships and capture *all* impacts of a specific change concurrently for new advanced aircraft. Certain basic, accepted (empirical) relationships should be acknowledged and proven to be correct in this environment. Figure 3 depicts these relationships in a design environment for a compressor. However, more importantly, other non-documented impacts will show up. The research anticipates to alleviate the designers worry of known unknowns and might bring to the forefront current unknowns (refer to Figure 4). Furthermore, the methodology should allow to capture advances such as the flutter/divergence prediction and the impact a structural change has on these properties. Ideally, a *dynamic* environment should be created which allows the designer to play "what-if" games.

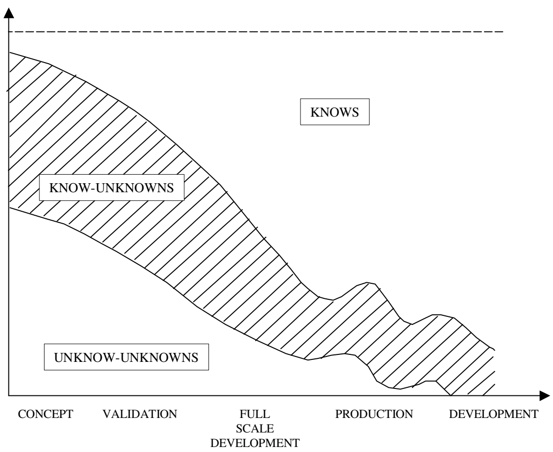
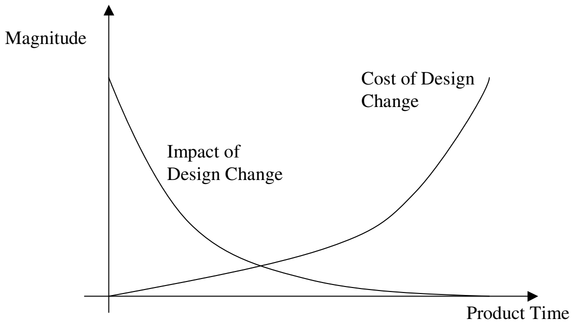


Figure 4: Design Knowns and Unknowns[10]

The goal of the current research is to increase knowledge and freedom early in the design. This objective is also known as the paradigm shift in design. During the 1960s, a study conducted by Boeing showed that the majority of the cost of a design gets locked in during the early stages of design, also referred to as "cost committed." The behavior is logically explained when considering designer freedom and the cost to change a design (redesign) on the same time scale (refer to Figure 5).[11]

In the past decade, there has been considerable effort to balance performance versus cost. The shift was further stimulated by the increase in computing power and advances in parametric and probabilistic design allowing more knowledge to be brought forward in the design process. This allowed the designer to make better informed decisions, effectively allowing the paradigm shift to take place. The new objective function in this perspective became affordability, not straight performance specs.[12]

As a result, the goal of this research is bi-fold: introducing more knowledge for the designer up front to help him make good decisions and secondly, try-



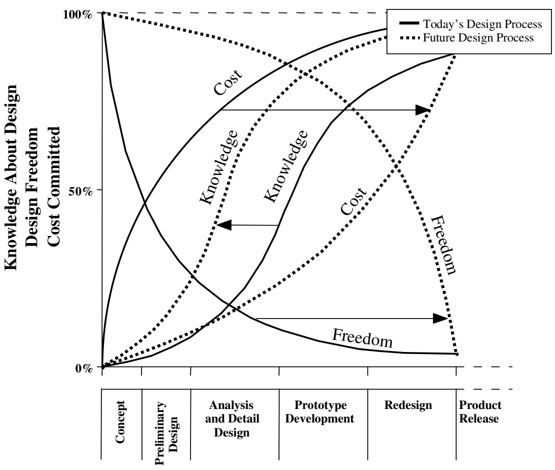


Figure 6: The Paradigm Shift[13]

ing to keep the design space open as long as possible to reduce committed cost. This paradigm shift is illustrated by the dotted lines and arrows in Figure 6.[13]

To conclude this section, the major requirements for this new methodology are: include dynamic and static aeroelastic analysis in a structural optimization subject to realistic constraints; incorporate a high-fidelity physics-based analysis code; and increase decision-making capability by generating a knowledge database in a dynamic environment.

Tools to Design for Aeroelasticity

Past research efforts have tried to create design tools that can be used at the conceptual level to increase the designer's knowledge of a system. These codes generally use simplifying theories and models. Overall, the results obtained from these tools are fairly good and have been validated with finite element models and experiments. These tools remain stand-alone codes though (i.e. they are not integrated in a design environment.) Their usage also requires a good knowledge of applied model simplifications and code assumptions. Possible modeling techniques include flat plates,[14] box beams,[15] or finite element type models, including unsteady aerodynamics.[16] Additionally, most research does not consider dynamic aeroelasticity (flutter) calculations, a notable exception being Mukhopadhyay's interactive flutter calculation program.[17] Mukhopadhyay however locks in the design space by specifying that the wing has to be a conventional cantilevered wing with straight leading and trailing edge.

This lack of knowledge requires physics-based tools to predict aeroelastic behavior of flight vehicles. Neural networks or statistical tools such as design of experiments (DOE) have been developed and can be used to generate the required information with these sophisticated codes.[13] Thus a new design database is created for a specific vehicle. This process should be clear and transparent to the designer such that the developed tool does not become a black box. In other terms, the aeroelastician "must develop insight into the physics of a problem so that the wide use of computers and black boxes can be a real blessing rather than a reliance on black magic."[18]

Finite element is the tool of choice for the structural design of the wing because of the required level of accuracy to warrant the effort and give new insights. The reasons this has not happened so far is because of the computing times associated with finite element models and the time spent setting up the finite element model input files.[19] The first aspect becomes less and less of a problem with faster computers and parallel computing becoming available. The second aspect highlights the need for an automated finite element input file generator. The latter was also recognized by DeLaurentis et al[2] as being the most critical parametric tool.

Nevertheless, there is still the classical trade-off in design modeling and analysis: efficiency versus accuracy.[20] Hence, if a design of experiment approach is to be considered, the large number of executions can be prohibitively expensive when using a finite element code. This is especially true when calculating the dynamic properties of the wing. Consequently, the need for quicker methods are obvious, and the method proposed tries to address this need.

Metamodels in Design

Central in this research is the capability to model the system in question. The need for physics-based models has been shown in the previous sections, especially for revolutionary and exotic concepts that lie outside the range of validity of regression-based equations. Examples include finite element models or computational fluid dynamic models. However, a drawback of the implementation in a parametric environment is the execution time as mentioned before. This problem can be remedied by using models of these models, or *metamodels*. Metamodels map the model output to the model input. The additional implementation of design of experiments and response surface methodology (RSM) allows to generate these disciplinary metamodels in a more efficient way.

$$R = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} x_i x_j + \epsilon \quad (1)$$

There is a limitation associated with this approach though. Three potential approaches to mitigate this are currently under consideration.

1. Even when all variables are important to the outcome of the response, there needs to be a distinction between this and the variability of the response. The variability might only be affected by a smaller number of inputs. So, although *all* inputs are important for the response, not all are as important for the response variability. If this is the case, fewer inputs need to be correlated to the response, hence effectively reducing the design of experiments and increasing the response surface accuracy. To investigate this, screening designs can be performed on the inputs, which are simplified design of experiments that only capturing the main effects of inputs on the response.

2. The response surface is limited to the second degree due to the high number of terms that arise from increasing the order for a large number of inputs (see Equation 1). Table 1 shows a summary of different design of experiments formulations and the required number of runs for a problem consisting of seven variables, where n is the number of factors in the equation. It is possible though to do a transformation on the variables to obtain higher order equations without running more cases. McDonald et al[21] have studied these transformations extensively.

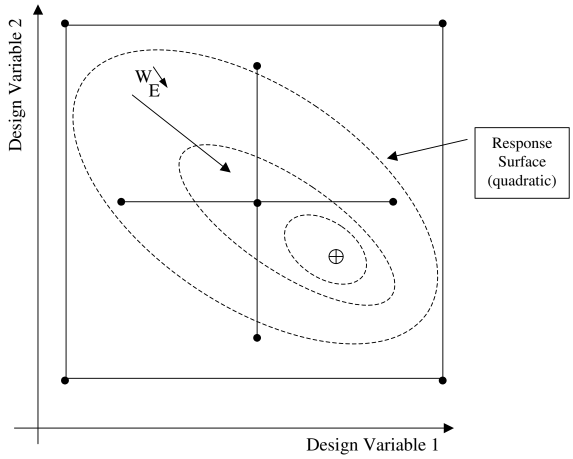


Figure 7: Classical Design of Experiments (Central Composite Design)

   Although they obtained improved fitting of the response, it generally did require some knowledge of the system behavior to do this wisely.

3. The advantageous part of the response surface methodology is that the effect of the inputs is very clear and visible through the response surface equation. Other techniques could be investigated that combine the advantage with other techniques. McDonald et al proposed the use of kriging. Kriging assumes a polynomial model (which would be our response surface) and a certain departure from that[22, 23]:

$$Y(x) = \sum_{j=1}^{k} \beta_j f_j(x) + Z(x) \quad (2)$$

   This departure $Z(\cdot)$ represents the realization of a stochastic process with assumed mean zero and covariance:

$$V(w,x) = \sigma^2 R(w,x) \quad (3)$$

   between $Z(w)$ and $Z(x)$ where σ^2 is the process variance and $R(w,x)$ is the correlation.

Scharl has shown that other techniques like neural networks (NN) do well at modeling complex systems.[12] Nevertheless, it is questionable if these even more intense modeling techniques can be used with the computationally expensive dynamic analysis that has to be performed. Consequently, the only

Table 1: Number of Analysis Runs for Several Designs of Experiments[13]

DOE	7 Variables	Equation
3-level, Full Factorial	2,187	3^n
Central Composite Design	143	$2^n + 2n + 1$
Box-Behnken	62	-
D-Optimal Design	36	$\frac{(n+1)(n+2)}{2}$

modeling technique available is the classical design of experiments since it provides a means to model a system with the least amount of runs necessary. The research will try to overcome the associated limitations with further refinement.

The classical design of experiments setup is depicted in Figure 7. In a two-dimensional space, the highlighted points, illustrating a central composite design here, would be calculated and the response at these nine points is used to predict what happens inside the square. The dashed line is the quadratic response surface. The response is chosen to be empty weight.

The finite element code ASTROS (Automated Structural Optimization System) is an analytical code, meaning that the program calculates the sensitivities of output to input analytically. This is a great time savings if sensitivities are needed, since otherwise a finite-differencing approach would have to be employed. So far, metamodels have relied solely on the response of the model. A new approach is to also use the derivative information,[24] called the global sensitivity equation (GSE) and is mainly used in multidisciplinary optimization. There, multiple executions of a code are also needed, and it is easier to describe the system with this global sensitivity equation, updating the response surface equation coefficients at greater run-intervals.

The global sensitivity equation approach has been used successfully,[25, 26] the limitations lie in knowing when this sensitivity information breaks down, i.e. what are the ranges of validity (refer to Figure 8). Either if the design space is small enough or there is a fast way to establish these ranges, this approach is unusable.

The idea of using derivative information is fairly new. This innovation is believed can and should be used since it is readily available in ASTROS. There are two distinctive applications of this information. Firstly, it would be used to generate the wanted "what-if" environment.[24] The optimum region for the design space can be found with the design of experiments approach and then those optimum settings could be run in ASTROS to generate the sensitivities for that point allowing further detailed optimization. This approach is depicted in Figure 9.

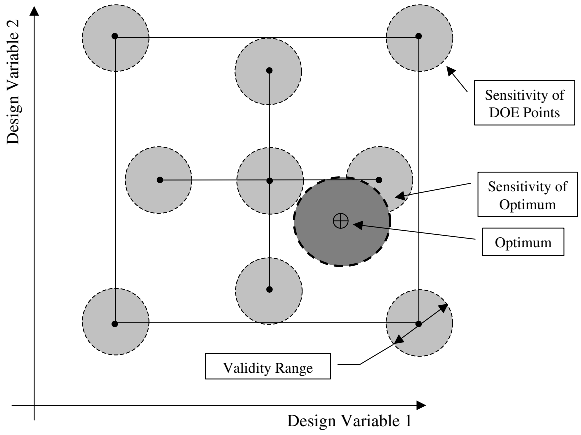


Figure 8: Global Sensitivity Equation Approach

Secondly, since the derivative information is also available at the calculated points, the response surface could be improved. The surface would not only know what its value should be at the calculated points; it would also know how to approach that point (refer to Figure 10). This, even if a minimal effect, should help offset the use of *only* a second order degree. Either accuracy can be increased for a given number of runs or the same level of accuracy can be achieved with fewer runs.[27]

For a standard response surface the equation coefficients $\mathbf{b}$ turn out to be[28]:

$$\mathbf{b} = \{\mathbf{X}^T\mathbf{X}\}^{-1}\mathbf{X}^T\mathbf{y} \tag{4}$$

where $\mathbf{y}$ are the function values and $\mathbf{X}$ is the design matrix.

For the incorporation of the derivatives a weighted least squares fit is used. For brevity only the resulting equation is displayed. For a more rigorous approach the reader is referred to van Keulen et al. The use of the weighing matrix $\mathbf{W}$ manifests itself as follows:

$$\mathbf{b} = \{\mathbf{X}^T\mathbf{W}\mathbf{X}\}^{-1}\mathbf{X}^T\mathbf{W}\mathbf{y} \tag{5}$$

The matrix $\mathbf{W}$ is defined for each experimental run and determines the importance of the derivative info at that point with respect to the function value. To compare accuracy the error measures defined in Equations 7 and 8 are used, where z is an arbitrary response function. It was demonstrated that the accuracy can be of the same or higher order. The

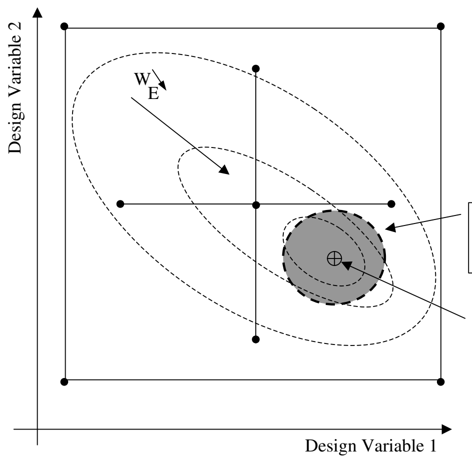


Figure 9: Combined Global Sensitivity Equation and Design of Experiments Approach, Part 1

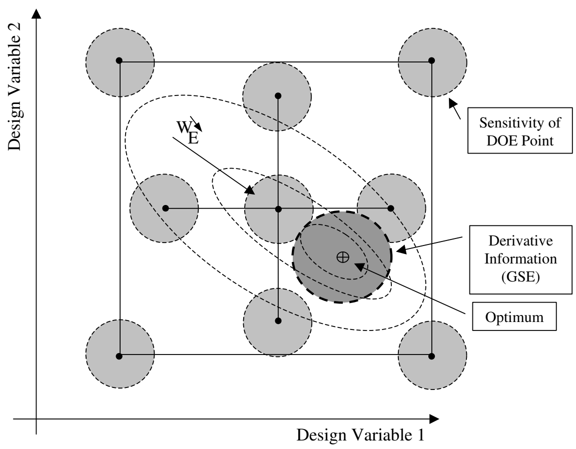


Figure 10: Combined Global Sensitivity Equation and Design of Experiments Approach, Part 2

figures with the response surfaces were all based on nine experimental runs and is shown in Figure 11 with the arrow. The dotted surface in Figures 12 through 14 was the "exact" surface (using Equation 6).

$$Response = 10+2X_1-2X_2+2X_1X_2-5X_1^2-6X_2^2 + 2X_1^3 + X_2^3 + X_1^2X_2 - X_1X_2^2 \quad (6)$$

$$MS(z) = \sqrt{\frac{1}{n_{tot}}\sum_{i=1}^{n_{tot}}(z_i - \hat{z}_i)} \quad (7)$$

$$LMS(z) = \log\Big(MS(z)\Big) \quad (8)$$

However, it is clear that this is very problem dependent and the use of **W** seems to imply that a certain rigidity is introduced. This is especially true in this simple problem and for the second order problem (Figure 13). The third order derivative response equation seems less prone to this effect (Figure 14). Nonetheless, the approach seems promising for more complex multi-dimensional problems.[27] They also note that the use of higher order response surfaces might be needed to show the full potential of the approach. Different approaches to use gradient information might have to be pursued when the above approach is not successful.[29]

Lastly, it should be noted that the sensitivities in ASTROS, $DOBJ_i$ in the ASTROS theoretical manual,[30] are only provided for the ASTROS objective function of weight, F, with respect to the design variables, v_i (see Equation 9[30]). These design variables are rod areas, element thicknesses, concentrated masses, stiffnesses, and so forth. However, the design variables at the conceptual system level are aspect ratio, sweep. Hence, transformations are needed which will link the ASTROS design sensitivities to system level sensitivities.

$$\frac{\partial F}{\partial v_i} = DOBJ_i \quad (9)$$

Modeling Aeroelasticity

The section will focus on the design of experiments approach and the methodology to incorporate ASTROS while minimizing the associated computational expense. A few options are pursued at this time. The research forks into a partitioned and non-partitioned approach at this time.

Non-Partitioned Approach

Here, the problem of "aeroelasticity in design" would be approached as one complex problem. The design of experiments methodology wraps around ASTROS, which handles the aerodynamics internally. A side-note is required here. Researchers have been skeptical on the reliability of ASTROS when calculating aeroelastic properties. This problem is acknowledged in the research as that one of the weak points of ASTROS is its aerodynamic module.[19] At this point, the solution was to opt for the

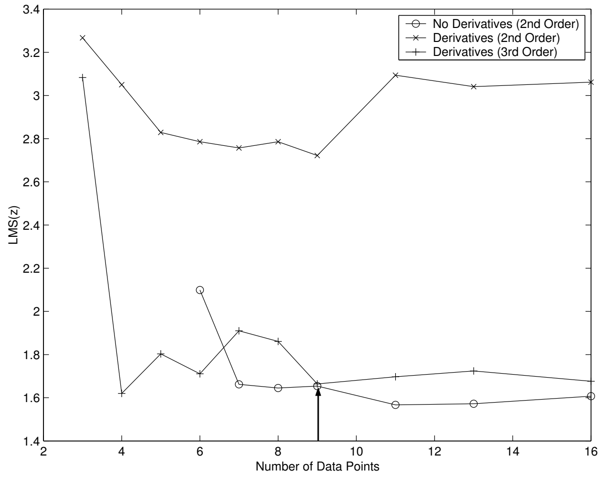


Figure 11: Accuracy Comparison of Response Surfaces

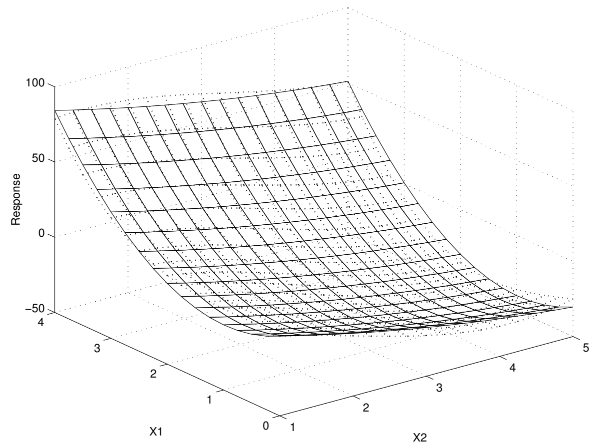


Figure 12: Plot of Predicted Surface (No Derivatives, 2^{nd} Order)

high-fidelity ZAERO toolbox which interfaces readily with ASTROS instead of opting for a physics-based approach for the aerodynamics (i.e. computational fluid dynamics). There are two distinct paths to optimization at this point.

Discrete Optimization

The first approach uses classical, discrete optimization in ASTROS. Static features, such as stresses and strains but also static aeroelasticity, have been treated with the discrete approach. However, as in most optimization schemes for the dynamic response of structures, the optimization is treated from a modal point of view.

The main reason for these different optimization options for static and dynamic analysis, was that the modal approach for statics might yield erroneous results in cases of concentrated loads and local structural changes.[31]

For each boundary condition, the procedure transforms the steady aerodynamic influence coefficient ($[AIC]$) matrix to f-set structural coordinates (unconstrained, free degrees of freedom set) and added to the structural stiffness matrix, $[K_{ff}]$. Note that these f-set structural coordinates are typically based on thousands of degrees of freedom (DOF) in realistic applications. A new non-symmetric stiffness matrix $[KA_{ff}]$ is then formed and introduced in the aeroelastic trim equations. The reduction to the a-set (unconstrained, free degrees of freedom, analysis set) and solving for these equations subsequently requires non-symmetric decomposition of large matrices.

Modal-based Optimization

The alternate approach would make use of the modal state-space approach for static optimization developed by Karpel et al.[31] This allows the optimization process to use a modal database for static and dynamic aeroelasticity, reducing the problem orders of magnitude.

The modal approach to structural optimization is based on using a set of low-frequency normal modes of the baseline structure as a fixed set of generalized coordinates throughout the optimization process.[32] The implementation in ASTROS is as follows: instead of keeping the modal coordinates fixed, they are changed in each design step, but the new set is assumed to be a linear combination of the baseline set. This approach extracts the eigenvalues and modes of the original none-optimized model satisfying the following:

$$[K_{aa}][\phi_{ai}] = [M_{aa}][\phi_{ai}][\Omega] \qquad (10)$$

with $[\phi_{ai}]$ the set of n_i calculated baseline modes defined in the a-set structural coordinates and $[\Omega]$ a diagonal matrix of n_i eigenvalues. The basic assumption of the modal approach is that the structural displacements during structural response to external excitation can be adequately expressed as a linear combination of baseline modes:

$$\{u_a\} = [\phi_{ai}]\{\xi\} \qquad (11)$$

where $\{u_a\}$ is the a-set structural displacement vector and $\{\xi\}$ is the vectors of generalized displacements.

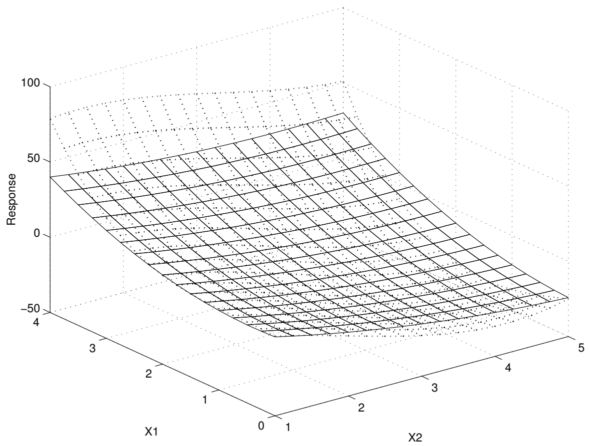


Figure 13: Plot of Predicted Surface (Derivatives, 2^{nd} Order)

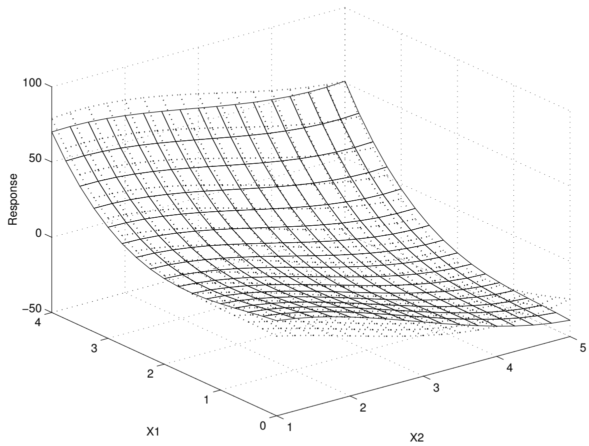


Figure 14: Plot of Predicted Surface (Derivatives, 3^{rd} Order)

This approach has been proven to produce very high accuracy in several realistic static-aeroelastic design studies.[33] Another advantage of this approach allows the immediate incorporation of a controls model leading to aeroservoelasticity.[33]

Partitioned Approach

As most aeroelasticians know, aeroelastic phenomena are an interaction between aerodynamic, elastic and inertia forces.[34] This is also illustrated in Collar's triangle. Recently, Sobieski et al[35] described a method for the optimization of complex engineering systems using decomposition. The research leading to the Bi-level Integrated System Synthesis (BLISS) was motivated by the need to distribute the work over many computers, enabling simultaneous optimization. Given this problem, the considered system is split according to the core programs that each handle a distinct subproblem. In this case it is proposed to decompose the aeroelastic problem according to each discipline from Collar's triangle.

Using the nomenclature of Sobieski et al, there is a vector Z which captures the variables common to all disciplines. The X_i vectors are local variables and only of importance to the individual discipline. Finally $Y_{i,j}$ are the variables from j used in discipline i. These latter ones are the coupling variables.

Optimization of a multidisciplinary system by decomposition, is a way to simply decouple the problem by sending the disciplinary outputs to the system level and letting the system level generate all disciplinary inputs.[36] Subsequently, since each discipline works independently of the other ones, they

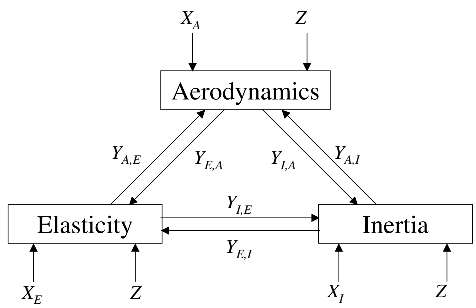


Figure 15: System of Coupled Black Boxes

can be optimized for an objective function F_i specific to that discipline shown in Equation 12. The objective function for the i^{th} black box is a linear combination of that black box's outputs, f_k. The partial derivatives are measures of the contribution of each output to the discipline objective, F_i.

$$F_i = \sum_{k=1}^{TotalOutputs} \frac{\partial f_k}{\partial \hat{Y}_k} \hat{Y}_k \qquad (12)$$

As Sobieski et al remark[35]: this equation mathematically states that the contributing disciplines should not optimize for their own outputs. Rather, the disciplines use a composite, synthetic objective function which measures more correctly the influence of each discipline i to the entire system objective function and subject to local constraints and by changing local variables X_i. Eventually, each discipline will have a response surface for each output,

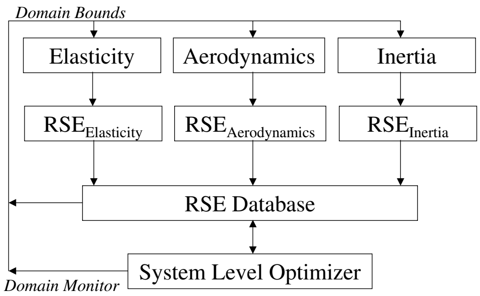


Figure 16: Bi-level Integrated System Synthesis Setup

function of the global variables Z, coupling variables $Y_{i,j}$, and sensitivity factors $\frac{\partial f_{\cdot}}{\partial Y_{\cdot}}$. It is noted, that this capitalizes on ASTROS' built-in capabilities to generate these sensitivities.

After the response surface generation is finished, the system level has at its disposition a database of response surfaces of all black box outputs (Figure 16). The system level then starts its optimization by changing Z. This optimization is subject to making the compatibility constraints equal to zero. These constraints are the differences between what the system level optimizer uses (called Y^*) and what the disciplinary response surfaces tell the system they should be after evaluation with the current Z (called $\hat{Y}$).

Furthermore, an added benefit of this method is that it inherently takes care of the required link between the ASTROS design variable sensitivities and the top level sensitivities.

Future Work

There are numerous airplanes, both currently investigated and in the recent past, that would benefit from increased knowledge at the conceptual and preliminary design level. Possible applications include the high speed civil transport (HSCT), supersonic business jet (SSBJ), Boeing's recent high-speed endeavor (the SonicCruiser). Other more futuristic applications include an oblique wing vehicle (offering possible sonic boom reduction) or a blended-wing body configuration (more likely to flutter because of the bigger wing and increased flexibility).

Initially, the research will focus on the implementation of BLISS. Work is already under way to validate the BLISS approach with ASTROS and ZAERO. This process includes the development of the automated grid point generation for ASTROS and logic to generate the response surfaces for each discipline.

Summary

A historic perspective was given of aeroelasticity in design. Current design practices were reviewed and put in the light of newly developed tools and insights. Furthermore, the concept of metamodeling was introduced and how an aeroelastic designer might benefit from their implementation. The disadvantages of response surfaces is discussed and a potential solution for these drawbacks is highlighted by including sensitivity information. The proposed use of ASTROS as the finite element code allows easy integration of this modification. Since ASTROS is an analytic code, no additional experiments are needed to obtain the derivative information and mitigate the response surface problem.

Lastly, an implementation scheme was proposed in both a partitioned and non-partitioned approach. The partitioned approach relied on the bi-level integrated system synthesis to separate the overall system considerations from the detail level considerations. The latter was chosen for future research work as it decouples the system in its natural disciplines.

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